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A comparison of global agricultural monitoring systems and current gaps

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ABSTRACT

Global and regional scale agricultural monitoring systems aim to provide up-to-date information regarding food production to different actors and decision makers in support of global and national food security. To help reduce price volatility of the kind experienced between 2007 and 2011, a global system of agricultural monitoring systems is needed to ensure the coordinated flow of information in a timely manner for early warning purposes. A number of systems now exist that fill this role. This paper provides an overview of the eight main global and regional scale agricultural monitoring systems currently in operation and compares them based on the input data and models used, the outputs produced and other characteristics such as the role of the analyst, their interaction with other systems and the geographical scale at which they operate. Despite improvements in access to high resolution satellite imagery over the last decade and the use of numerous remote-sensing based products by the different systems, there are still fundamental gaps. Based on a questionnaire, discussions with the system experts and the literature, we present the main gaps in the data and in the methods. Finally, we propose some recommendations for addressing these gaps through ongoing improvements in remote sensing, harnessing new and innovative data streams and the continued sharing of more and more data.

1. Introduction

Achieving food security is high on the agenda of the Sustainable Development Goals (United Nations, 2015), in particular SDG 2 to "End hunger, achieve food security and improved nutrition, and promote sustainable agriculture". Despite significant advances in sustainable global agricultural production, this remains a key challenge due to the complex interaction between factors such as extreme weather patterns, rising levels of population and wealth, water scarcity, increases in energy costs and civil conflicts (Godfray et al., 2010). Between 2007 and 2011, there were significant increases in world food prices of major commodities (i.e. maize, wheat, rice), which sparked political and social unrest around the world (UN, 2011). Shifts towards a meat-based diet in many developing countries, increases in oil prices, which had a

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knock-on effect on fertilizer prices, financial speculation and insufficient stocks of major grain commodities in the main agricultural producing countries were suggested as possible drivers, among others (Adam and Ajakaiye, 2011; Headey and Fan, 2010). To better prepare for disruptions in food supply and global crop market price fluctuations of the types witnessed over the last 10 years, timely and accurate information on current and forecasted global food production is needed (Wu et al., 2014). Improved monitoring will enable more accurate forecasting of commodity prices and a better understanding of the key risks in food supply, helping to reduce global food insecurity (Justice and Becker-Reshef, 2007).

Agricultural monitoring on a regional and national level has been in place for decades, e.g. the Global Information and Early Warning System (GIEWS) from the Food and Agriculture Organization (FAO) of the United Nations, the Famine Early Warning Systems Network (FEWS NET) from the United States Agency for International Development (USAID), CropWatch in China, and the Monitoring Agriculture with Remote Sensing (MARS) system from the European Commission (EC). These systems have tended to operate somewhat independently with little sharing of information, where the focus has been on either food security for developing countries or food production for the global market. The United States Department of Agriculture's Foreign Agricultural Service (USDA-FAS) was the first system to provide globally comprehensive information on crop production and crop condition (Becker-Reshef et al., 2010). These crop production estimates are also used as economic indicators, for early warning alerts, in foreign aid assessments for food import needs, in commercial market trends and analysis, and in trade policy and exporter assistance. However, it was recognized that national and regional monitoring systems cannot effectively monitor agriculture at all scales so there needs to be greater coordination and sharing of information, i.e. a Global Agricultural Monitoring System of Systems (Justice and Becker-Reshef, 2007). The Group on Earth Observations (GEO) became the ideal body to launch the flagship initiative GEOGLAM (GEO GLobal Agricultural Monitoring), which has become the mechanism for bringing together key players in the global agricultural monitoring community, to share information internationally, and to produce two regular bulletins (one for the Agricultural Market Information System (AMIS) and one for Early Warning covering approximately 95% of the world's croplands) that represents consensus of the current situation globally. Other initiatives have also been launched that support GEOGLAM, e.g. the Anomaly Hot Spots of Agricultural Production (ASAP) system, which started in 2017 (Rembold et al., 2017).

To gain a better understanding of the current state of global agricultural monitoring, eight major operational systems were identified that either play an important role in regional or global agricultural monitoring or which contribute to GEOGLAM at an international scale. This paper also provides a comprehensive update to the previous review of agricultural monitoring systems provided by Atzberger (2013). Each of these systems are briefly described along with the results from two questionnaires that were used to gather information about each system. The first focused on a series of questions regarding the system inputs and outputs as well as general questions about geographical scope, stakeholders, interactions with other systems, etc. A second questionnaire was used to gauge the importance of (i) different data inputs, which are then described along with state-of-the-art developments from the literature (Section 4.1) and (ii) perceived gaps in methodologies, which are described in Section 4.2. The paper concludes with an outlook to the future, including recommendations for how these gaps might be addressed.

2. Description of the main global and regional scale agricultural monitoring systems

At present there are eight operational regional and global scale agricultural monitoring systems that provide information to stakeholders to support evidence-based decision making. A brief overview of each system is provided below in chronological order of their establishment. Some of these systems are part of more comprehensive food security monitoring initiatives (e.g. FEWS NET and GIEWS) but the aim of this paper is to focus on a comparison of the global crop production components.

2.1. Global information and early warning system (GIEWS)

Established in the early 1970s, GIEWS[1] was one of the first key global sources of information on food production and food security within FAO. The system provides regular bulletins of food crop production and markets on a global scale, as well as more specific regional reports based on intelligence from FAO's regional and country offices. GIEWS includes a network of 115 governments, 61 non-governmental organizations (NGOs) and numerous trade, research and media organizations. The GIEWS team continuously monitors the world's food supply and demand situation, using geospatial data as an auxiliary variable to detect weather-related problems that could have an impact on food security in member countries. In addition to rainfall estimates and the Normalized Difference Vegetation Index (NDVI), GIEWS uses the Agricultural Stress Index (ASI), adopted in 2013, an indicator for early identification of agricultural areas that may be affected by dry spells or droughts (Rojas et al., 2011), which was designed to fill an information gap in the existing early warning system. Every ten days, the ASIS (ASI System) generates a map showing hotspots where crops are affected by water stress during the growing period, which are then verified by data from public institutions or using agrometeorological models based on data obtained from national meteorological networks, which ultimately show indicator convergence (Rojas, 2015).

2.2. Famine early warning systems network (FEWS NET)

In 1985, the FEWS NET system[2] was initiated by USAID to provide decision support to food assistance programs and relief agencies (Funk and Verdin, 2010). FEWS NET attempts to quantify both changes in the area planted as well as crop yield but does not monitor production directly (Brown, 2008). Currently covering 36 of the world's most food-insecure countries, the system not only publishes specialized monthly reports on current and projected food security but also provides timely alerts on emerging crises. FEWS NET follows a convergence of evidence strategy to achieve its goals. Data from field assessments, agro-climatology, market/price monitoring, nutrition surveillance and conflicts are combined to build scenarios, carry out livelihood analysis and produce information for effective decision support. In additional to quarterly outlook reports, FEWS NET updates scenarios monthly as new information becomes available. FEWS NET draws heavily on agro-climatology data for its food security analysis, relying mostly on anomaly analysis (Senay et al., 2015).

2.3. MARS crop yield forecasting system (MCYFS)

In 1992, the MARS program of the JRC developed the operational MARS Crop Yield Forecasting System (MCYFS) to fill the need for operational estimates of area, yield and production at pan-European level for EU member states. It is operated under the mandate of the European regulation No 1306/2013 (Art. 6 and 22). This regulation stipulates an agricultural monitoring system and production and yield forecasts to manage agricultural markets. As a decision support system, the MCYFS provides independent and evidence-based information on the status of annual crops in the EU and neighboring countries by monitoring crop growth and forecasting crop yields (Supit et al., 1994; Baruth et al.,

[1] http://www.fao.org/giews/en/.
[2] http://www.fews.net/.

2008; Gallego et al., 2010; Duveiller, 2012; Boogaard et al., 2013; Bojanowski et al., 2013; López-Lozano et al., 2015). The MCYFS is based on near real-time acquisition and processing of three main data sources: weather data (observations and forecasts), crop model simulations, and biophysical parameters derived from satellite remote sensing to monitor the crop status. All these data plus a time series of historic area and yield statistics are used within a statistical yield forecasting process. Monthly MARS bulletins are published that provide an overview on the development of the main crops and areas of concern including yield forecasts for cereals, oilseeds, and tuber crops, a pasture analysis and country specific analyses. Near real-time and historic information on weather conditions and the progress of crop growth can be visualized via the JRC MARS Explorer[3]. Maps for several weather and crop indicators are available and the information is updated three times per month.

2.4. CropWatch

CropWatch[4], which is led by the Institute of Remote Sensing and Digital Earth at the Chinese Academy of Sciences, evaluates national and global crop production. Started in 1998, the aim of this system is to provide timely, reliable and independent predictions of crop conditions and production, both within China and globally, in order to plan crop imports, exports, and prices and ensure national food security (Wu et al., 2014). Since 2013, CropWatch has been releasing bulletins internationally. Four spatial levels are considered: global, regional, national (thirty-one key countries including China), and sub-national (for the nine largest countries). These thirty-one countries encompass more than 80% of both production and exports of maize, rice, soybean and wheat. Global patterns of growing conditions are analyzed using indicators for rainfall, temperature, photosynthetically active radiation (PAR) as well as potential biomass. At the regional scale, other indicators such as the Vegetation Health Index (VHI) and the Vegetation Condition Index (VCI) are used to characterize the crop situation, farming intensity and stress. CropWatch also carries out detailed crop condition analyses at the national and sub-national scale with a comprehensive array of variables and indicators to derive food production estimates (Wu et al., 2015).

2.5. United States Department of Agriculture-Foreign Agricultural Service (USDA-FAS)

After Hurricane Mitch devastated Honduras in 1998, the Honduran Ministry of Agriculture needed near real-time information on agriculture during the reconstruction period. Hence in 2001 the Foreign Agricultural Service (FAS) of the US Department of Agriculture (USDA)[5] began the Crop Explorer service, which provides remote sensing-based information used by agricultural economists and researchers to predict global crop production. The system automates the extraction and processing of agro-meteorological indicators from MODIS (Moderate Resolution Imaging Spectroradiometer), TOPEX/Poseidon and Jason-1 satellites to publish data visualization products every 10 days. FAS also has the responsibility of providing market intelligence in the form of timely, objective, unclassified, global crop conditions and production estimates, for all major commodities, for all foreign countries. These estimates are an integral part of the World Agricultural Production and World Agricultural Supply and Demand numbers used by the US Office of Management and Budget (OMB) as economic indicators. To accomplish this task, FAS synthesizes information from its global network of marketing experts, agricultural economists, meteorologists and remote sensing scientists. In addition to the crop production information from foreign government reports and field visits, remote sensing is used to help verify these reports.

A series of data sets coupled with meteorological data and crop models have significantly improved the USDA-FAS' operational capacities to monitor and forecast global crop production. These data sets come from the Global Agricultural Monitoring (GLAM) project, initiated in 2002, which is a collaborative research project between USDA-FAS, the University of Maryland (UMD), the Global Inventory Monitoring and Modelling Studies (GIMMS) at NASA, and South Dakota State University (SDSU) (Becker-Reshef et al., 2010). The GLAM project focuses on the integration and analysis of MODIS data products to feed the USDA-FAS decision support system. The initiative combines multiple satellite data resources including NDVI from GIMMS and MODIS, among others. In USDA-FAS, change in crop area estimates and mid-season dominant crop masks are computed using semi-automated classification algorithms and remote sensing data. Mid-season to end-of-season yield estimates and maps are produced using regression and analog year algorithms derived from MODIS NDVI data.

2.6. GEOGLAM

As mentioned in the introduction, GEOGLAM[6] is a flagship initiative from GEO, which was endorsed by the G20 in 2011 to provide the Agricultural Market Information System (AMIS) with an assessment of crop growing conditions, crop status and agro-climatic conditions that may have an impact on global production of wheat, maize, rice and soy. Documented in the Crop Monitor bulletin, these assessments have been produced operationally since September 2013. Crop Monitor assessments are conducted during the final ten days of each month to ensure timely information for the Crop Monitor. A conference call is held each month with a group of international experts to discuss and review these assessments, which have been generated from a variety of independent, yet complementary, sources and to provide an opportunity to reach consensus on any discrepancies. The consensus information is then compiled into a report, which is reviewed iteratively by the partners.

2.7. World Food Programme Seasonal Monitor

Since 2014, the Seasonal Monitor system[7] of the World Food Programme (WFP) has been operational, primarily to monitor growing season status and to provide early warning of conditions detrimental to crop and pasture production within WFP regions of interest. The reason for the development of this system was the need for more detailed information than was available from other systems as well as the ability to produce tailored outputs for internal customers. The system derives indicators from near real-time rainfall estimates (CHIRPS) and NDVI (MODIS) data. A range of outputs is produced, mainly aggregations of rainfall amounts at varying time scales, dates of onset of the growing season and vegetation index, as well as anomalies of most parameters. The main outputs of the system are region specific reports with an approximate monthly frequency describing the current growing season conditions and providing an outlook for the months ahead based on available seasonal forecast information. Another perspective on growing season monitoring is provided by Dataviz[8], a visualization platform from WFP, that includes data from the Seasonal Explorer where users can obtain charts of time series of seasonal rainfall and NDVI values and anomalies for administrative regions: from administrative Level 0 (country), Level 1 (state, province, region, governorate, etc.) and Level 2 (district, locality, county), as well as data from the Economic Explorer, where price and price-forecast information is also shown. The data from the Seasonal Monitor can be obtained for the

[3] http://agri4cast.jrc.ec.europa.eu/mars-explorer/.
[4] http://www.cropwatch.com.cn/.
[5] https://www.fas.usda.gov/.
[6] http://www.geoglam.org/index.php/en/.
[7] https://www.wfp.org/content/seasonal-monitor.
[8] http://dataviz.vam.wfp.org/.

entire administrative unit or for only the areas covered by cropland or pasture (according to a land cover layer).

2.8. ASAP (Anomaly Hot Spots of Agricultural Production)

The final system is the Anomaly Hot Spots of Agricultural Production (ASAP)[9], launched by the Joint Research Centre (JRC) of the European Commission (EC) in June 2017. This information system was developed both for EC use and for making contributions to multi-agency information systems such as GEOGLAM. ASAP focuses on finding areas where unfavorable growing conditions for both crops and rangelands may represent a potential food security problem (Rembold et al., 2017) and informs EU-supported food security assessments such as the Integrated Food Security Classification and the Global Report on Food Crises. There are two parts to this system. In the first part, rainfall estimates and the NDVI derived from remote sensing are used to automatically generate warnings at the first sub-national level regarding potential problems with crop and rangeland production globally. These early warnings are issued every 10 days when new rainfall and NDVI data become available. The second part of the system involves using agricultural monitoring experts to verify these 'hotspots' of potential food security problems for around 80 countries with high risk of food insecurity; these assessments are updated on a monthly basis. The main added value of the ASAP system is that it analyzes the available Earth Observation (EO) and weather data and turns this into short warning messages that do not require a background in geospatial data analysis to be useful for decision makers. The ASAP complements the information available through the MCYFS, covering food insecure areas outside of Europe.

3. Comparison of the main global and regional scale agricultural monitoring systems

To compare the eight systems, a questionnaire was used to collect information about each system, which can be found in the Supplementary Information. Table 1 summarizes the data and models used by each system while Fig. 1 quantifies the number of sources of input data used. Fig. 2 indicates the degree to which the different systems use five main sources of information, i.e. meteorological data, crop models, optical satellite remote sensing, analyst input and other auxiliary data sets.

The results show that all of the systems make use of meteorological data and remote sensing information although many of the meteorological data are derived from remote sensing (Table 1). Only the MARS MCYFS uses interpolated data from stations while ASAP uses gridded meteorological data from atmospheric models. The sources of remote sensing used vary across the systems (Table 1), with CropWatch, USDA-FAS (Crop Explorer) and GEOGLAM using the highest number of different remote sensing products (Fig. 1). Each of the systems that use crop models employ different ones although GEOGLAM obtains inputs from FEWS NET and GIEWS in their crop condition modelling (Table 1). A range of different auxiliary data sets are used by each of the systems (Table 1) with GIEWS, MCYFS MARS, USDA-FAS (Crop Explorer) and CropWatch using > 10 different sources of additional data (Fig. 1). Almost all of the systems forecast crop conditions while some systems additionally forecast cropping intensity, i.e. the number of crops grown per year, crop area, crop yield, crop production and crop production anomalies or crop area affected by critical anomalies. The GIEWS and USDA-FAS systems additionally make forecasts of other data such as crop stage and start of the season while USDA-FAS also forecasts the number of dry days and has the highest number of forecasting outputs (Fig. 1).

Fig. 2 shows that no system relies entirely on any one type of input of the five shown, i.e. meteorological data, crop models, optical remote sensing, analyst input or auxiliary data. The USDA-FAS and FEWS NET make considerable use of all five sources while systems like Seasonal Monitor use mostly optical remote sensing data and analyst inputs, supplemented with meteorological data from remote sensing and auxiliary data. Of the remaining systems, the importance of meteorological data is evident, while crop models, optical remote sensing, analyst input and auxiliary data are of varying importance to the systems.

The system outputs and the dissemination across the different systems is summarized in Table 2. All the systems produce NDVI profiles and produce outputs related to anomalies. All the systems produce phenological analyses except for GEOGLAM and the Seasonal Monitor and only GEOGLAM does not produce rainfall profiles. All the systems produce some type of bulletin or report except for ASAP, which disseminates the information online via web services and GIS files. FEWS NET also disseminates many GIS layers used in their analyses, e.g. rainfall estimates, anomalies, the Water Requirement Satisfaction Index, etc. Except for GEOGLAM, which only produces the Crop Monitor, the other systems produce several outputs with USDA-FAS (Crop Explorer) producing the largest number (Fig. 1). Regarding the accuracy of the system outputs, there are few quantitative assessments available for the operational systems considered here. One example is provided by Van der Velde and Nisini (2018; this Virtual Special Issue), who found that for the end-of-campaign MCYFS crop yield forecasts from 1993 to 2015, the lowest median mean absolute percentage error (MAPE) across all crops was obtained for Europe's largest producer at 3.73%, while the highest median MAPE was obtained for Portugal, at 14.37%. MCYFS forecasts generally underestimated reported yields, with a systematic underestimation across all member states for soft wheat, rapeseed and sugar beet forecasts. Forecasts generally improved during the growing season; both the forecast error and its variability tend to progressively decrease. Egelkraut et al. (2003) undertook a quality assessment of crop forecasts from the USDA and found that errors were larger for maize than soybeans, but similar to the MCYFS, the forecasts improved as the season progressed. The outputs from these systems clearly require more evaluation, which should be made transparent and published.

Four of the systems undertake their analysis at the national, sub-national and pixel level which also mirrors the resolution of their outputs. Other systems use combinations of either national/sub-national or sub-national/pixel, reflecting different information needs. FEWS NET also disseminates their output by livelihood zones. Five of the systems disseminate early warning information during the growing season on a dekadal (10-day) or monthly basis. Only the CropWatch system releases information on a quarterly and annual basis while the Seasonal Monitor aims to produce three reports per growing season. The dissemination schedule for GEOGLAM is very much driven by the need to provide information to AMIS on a monthly basis.

Table 3 contains other characteristics of the monitoring systems that were asked in the questionnaire. For example, the role of the analyst is quite similar across systems, e.g. they undertake different types of agrometeorological and statistical analyses, synthesize information from multiple sources and contribute to reports. However, some systems are more automated compared to others, e.g. WFP's Seasonal Monitor and the ASAP system require some degree of expert knowledge to judge how severe a drought is, for example, while the ASIS system produces a map that directly indicates where and how severe the anomaly is. In the future, these systems may require more automation in order to deal with the increasing amounts of big data. All of the systems have a mechanism for dealing with situations where information sources disagree, which are flagged by the analysts and generally involves expert intervention and cross-validation with additional data sources. GEOGLAM, in particular, has a transparent approach to finding consensus from the different system assessments and data sources. In fact, all of the systems contribute to GEOGLAM's Crop Monitor but there is also interaction and use of products between systems. Most of

[9] https://mars.jrc.ec.europa.eu/asap/.

Table 1
Data and model inputs used by each monitoring system obtained from the questionnaire. Check marks or text indicate that the systems use the data or model inputs while a dash indicates non-usage or non-applicability. The following acronyms are used to indicate meteorological sources: AM, gridded data from Atmospheric Model; RS, gridded data estimated by a RS-based model; I, gridded data interpolated from meteorological ground station data.

Data and model inputs			GIEWS	FEWS NET	MCYFS	CropWatch	USDA-FAS	GEOGLAM	Seasonal Monitor	ASAP
Meteorological data source used	Precipitation		RS	RS	I	RS	RS	RS	RS	AM
	Temperature		RS	RS	I	RS	RS	RS	–	AM
	Evapotranspiration		–	RS	I	RS	RS	RS	–	AM
	Solar radiation		–	RS	I	RS	RS	–	–	–
	Relative humidity		–	RS	I	–	–	–	–	–
	Wind speed		–	RS	I	–	–	–	–	–
	Snow coverage		RS	–	I	–	RS	–	–	–
	Total cloud cover		–	–	I	–	–	–	–	–
	Water vapor pressure		–	–	I	–	–	–	–	–
	Atmospheric pressure		–	RS	–	–	–	–	–	–
Remote sensing	Products	Vegetation indices (e.g. NDVI, VHI, fAPAR)	✓	✓	✓	✓	✓	✓	✓	✓
		Soil moisture, FAO-ASIS	✓	✓	–	–	✓	✓	–	–
	Sensors	Passive Radar (10–50 km) (e.g. SMOS, SMAP, SSM/I, TMI)	–	✓	–	✓	✓	✓	–	–
		Active radar (20 m – 50 km) (e.g.ASCAT, JASON, Sentinel 1)	–	–	–	✓	✓	–	–	✓
		Geostationary (5 km, e.g. FY2)	–	–	–	✓	–	–	–	–
		Coarse resolution optical (250 m – 1 km) (e.g. AVHRR, MODIS, Proba-V, FengYun-3)	–	✓	✓	✓	✓	✓	✓	✓
		Very high to high resolution optical (80 cm – 30 m) (e.g. Landsat, Sentinel 2, Gaofen1&2, ZY3)	–	✓	–	✓	✓	–	✓	✓
Crop models used	Water balance models (e.g. GWSI, WRSI)		✓	✓	–	–	✓	✓	–	✓
	Biophysical/simulation models (e.g.WOFOST, Wheat Ritchie (CERES), Sorghum Vanderlip and Reeves, GDD, Corn Hanway, FAO-ASIS, WARM for rice, etc.)		✓	–	✓	–	✓	–	–	–
	NDVI models		✓	–	✓	✓	✓	–	–	✓
	Statistical and bespoke models (e.g. FAO-ASIS)		✓	–	✓	✓	✓	–	–	–
Auxiliary data used	Cropland maps		✓	✓	✓	✓	✓	–	✓	✓
	Crop type		✓	–	✓	✓	✓	✓	–	✓
	Crop calendar		✓	✓	✓	✓	✓	✓	✓	✓
	Soil information		✓	–	✓	✓	✓	–	–	✓
	European Media Monitor outputs		–	–	✓	–	–	–	–	✓
	Agricultural Census		✓	–	✓	–	✓	✓	–	–
	Agricultural Surveys		–	✓	–	✓	✓	–	–	–
	Small area crop statistics		✓	–	✓	✓	✓	–	–	–
	Agricultural contacts		–	–	–	✓	✓	✓	–	–
	DEM		–	–	✓	✓	✓	✓	–	–
	Climate or agroecological zones		✓	✓	–	✓	–	–	–	–
	Surface water availability		✓	–	–	–	✓	–	–	–
	Commodity prices		✓	–	–	–	✓	–	–	–
	Soil map		✓	–	✓	✓	✓	–	–	✓
	Admin borders		✓	–	✓	✓	✓	✓	✓	✓
	Livelihood zones		✓	✓	–	–	–	–	–	–
	Windshield survey (field observation)		✓	✓	✓	✓	✓	✓	✓	✓
Forecasts from the system	Crop conditions		✓	–	✓	✓	✓	✓	–	✓
	Agro-climate/potential Biomass		–	–	–	✓	–	–	–	–
	Cropland utilization		✓	–	✓	✓	✓	–	–	–
	Cropping intensity		✓	✓	–	✓	✓	–	–	–
	Crop area		✓	–	–	✓	✓	–	–	–
	Crop yield		✓	✓	–	✓	✓	–	–	–
	Crop production anomalies		–	–	–	✓	✓	–	✓	✓
	Crop area affected by critical anomalies		✓	–	–	✓	✓	✓	–	✓
	Crop stage		✓	–	–	–	✓	–	–	–
	Season start		✓	–	–	–	✓	–	–	–
	Number of dry days		–	–	–	–	✓	–	–	–
	NDVI values		✓	–	–	✓	✓	–	–	–

AET = actual evapotranspiration; PET = potential evapotranspiration; ET = evapotranspiration; RH = relative humidity; DEM = digital elevation model; NDVI = normalized difference vegetation index; ASI = Agricultural Stress Index; GDD = growing degree days, VCI = vegetation condition index, TCI = temperature condition index, VHI = vegetation health index, RFE = rainfall estimate, SPAM = spatial allocation model, WRSI = water requirement satisfaction index.

the systems provide some open access to their GIS outputs, some are planning to open more of their data in the future while MCYFS MARS and GEOGLAM currently do not have any outputs that are openly available as GIS layers. The areas covered by the systems is largely global. FEWS NET has more activities in certain regions but their data sets offer global coverage while MCYFS MARS is more focused on Europe and neighboring countries. GEOGLAM also focuses on countries that cover around 95% of all cropped area. There is a wide range of stakeholders to whom the information is of interest including government ministries and EU departments, aid organizations, agribusiness

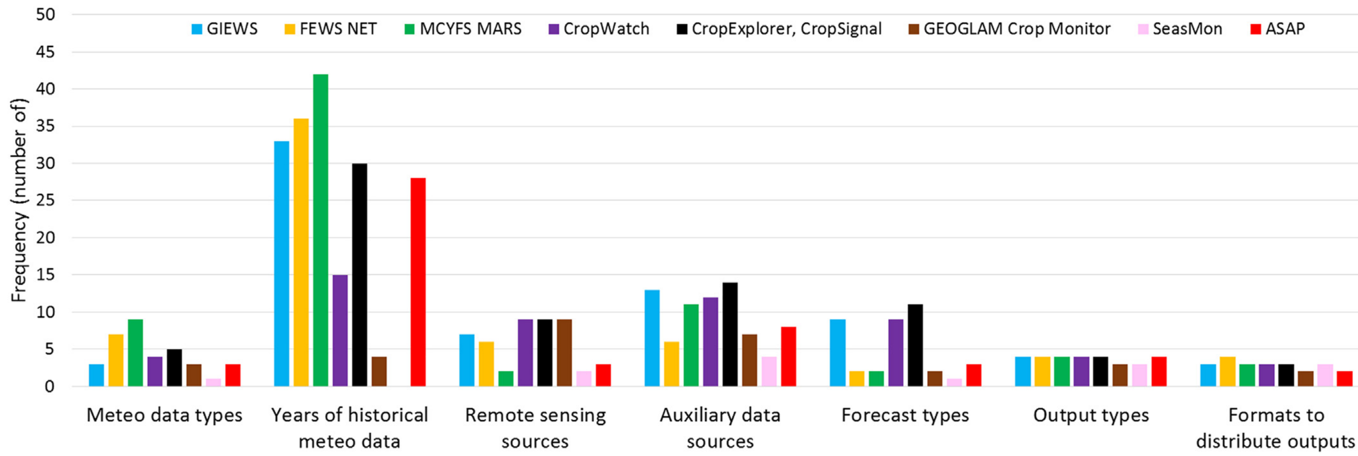

Fig. 1. Comparison of global and regional scale agricultural monitoring systems in terms of number of sources of input data used.

and other relevant industries and AMIS, as a direct user of the GEOGLAM Crop Monitor.

4. Gaps in agricultural monitoring needs

Discussions with each of the monitoring systems was initially used to determine what the current data gaps in agricultural monitoring are. To formalize this gap analysis, a second questionnaire was used to determine the importance of different data inputs to the system, including cropland maps, crop calendars, maps of cropping intensity and crop types, crop management data sets, meteorological data, and statistical and in-situ data on agricultural production, yield and area. These gaps, along with state of the art, are described in section 4.1. There was also a question about the main methodological gaps perceived by each system, which are summarized in section 4.2. This second questionnaire is provided in the Supplementary Information.

4.1. Data gaps

Fig. 3 summarizes the level of importance of different sources across all agricultural monitoring systems while Fig. S1 shows the breakdown of answers by individual system. Cropland maps, crop calendars, statistics on agricultural production and meteorological data are considered very to extremely critical by more than half of the systems. Each of these data gaps are now discussed in the sections that follow.

4.1.1. Cropland maps

Seven out of eight systems identified global cropland maps as being critical or very critical to their systems. Cropland is captured in one or more land cover types within global land cover maps although Fritz et al. (2011) have shown that there is considerable disagreement between the major land cover products with respect to cropland. Specific cropland maps have also been produced (Biradar et al., 2009; Pittman et al., 2010; Thenkabail et al., 2009; Yu et al., 2013) but each of these also has associated uncertainties in cropland definitions, the methods used, issues with spectral separation, particularly when there are seasonal effects, and cloud cover in certain regions when using optical data, etc. (Gong et al., 2016). Very fragmented landscapes typical of smallholder farmers will require higher resolution images to meet the accuracy requirements (Waldner and Defourny, 2017). The latest 30 m cropland map produced by Xiong et al. (2017) has an overall accuracy of 94% (defined as the percentage of correctly classified sample locations) but a user's accuracy of 68.5%, which is a class specific accuracy for cropland that indicates how often this class will actually be present on the ground so still requires improvement. Yearly updates are desirable, especially in regions where cropland can be very dynamic, such as the Sahel, but this is not yet available operationally on a global scale. ESA's Sentinel 2 for Agriculture (Sen2Agri)[10] project recently released an open source and portable toolbox to derive dynamic cropland maps in an operational fashion from Sentinel 2 and Landsat-8 time series (Matton et al., 2015; Valero et al., 2016), which shows promising results.

The global hybrid cropland map produced by IIASA and IFPRI (Fritz et al., 2015), the Unified Cropland Layer (Waldner et al., 2016), and the GLC-SHARE hybrid land cover product (FAO, 2015a) represent another approach in which multiple cropland or land cover products have been merged to produce the best characterization of cropland or land cover at a particular location. The IIASA-IFPRI product has also been calibrated using FAO statistics so that it can be used in global models that require official statistics. A similar approach has been used to build the cropland and rangeland maps of ASAP, where six global and 16 regional land cover data sets were compared at the country level using multi-criteria decision analysis to select the most suitable ones for agricultural monitoring (Pérez-Hoyos et al., 2017). As it is clear that more effort is required to accurately map the world's cropland, Waldner et al. (2015) have compiled existing cropland maps to highlight priority areas for improving cropland mapping.

4.1.2. Crop calendars

Similar to global cropland maps, global crop calendars were viewed as being critical to very critical by all of the eight systems although the MCYFS system uses only European ones. Crop calendars contain the planting and harvesting dates of different crop types for an area or region. These are useful for crop condition monitoring, crop type area estimation and crop yield forecasting and estimation, among other applications. Agricultural policies, the mobilization of food aid and the movement of commodities to market would also benefit from accurate knowledge of harvest timing. Furthermore, such information could contribute to the UN SDG goal 12.3 to reduce post-harvest losses (IAEG-SDGs, 2016).

FAO provides crop calendars for a large variety of crops for 44 African countries by agro-ecological zone (FAO, 2010). This type of information is traditionally gathered from household surveys and national censuses, which is time consuming to collect and maintain. Moreover, the use of agro-ecological zones fails to capture regional variations. As part of the MIRCA2000 data set, crop calendars were constructed for 402 spatial units from censuses, national reports and other relevant databases, using global monthly irrigated and rainfed crop areas (Portmann et al., 2010) as an input. A similar approach was taken by Sacks et al. (2010) but additional sources of sub-national data were used, and the full range of planting and harvesting dates in a

[10] http://www.esa-sen2agri.org/.

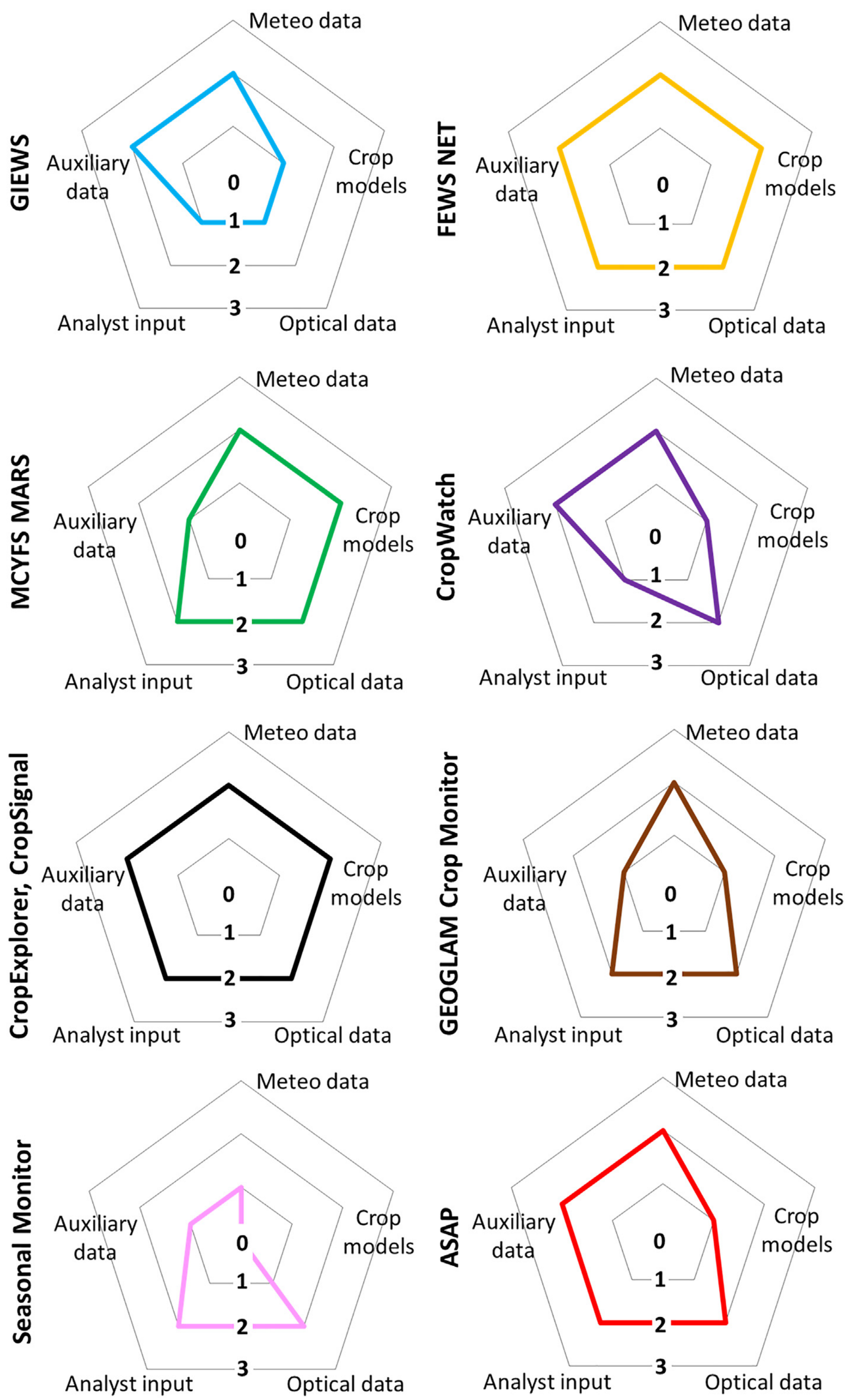

Fig. 2. Comparison of the global and regional agricultural monitoring systems in terms of the degree to which they use different sources of input data. The reference is the following: 3, exclusively; 2, a lot; 1, a little; and 0, not at all.

region were provided rather than the most typical one. Although both of these data sets are global, they have similar limitations to the FAO crop calendar, i.e. they fail to capture spatial variations due to the coarse resolution of the underlying national and sub-national data. More recently, Laborte et al. (2017) produced the global RiceAtlas with crop calendars for rice production.

Other approaches involve modelling of planting dates based on climate data (Stehfest et al., 2007; Sacks et al., 2010; Waha et al., 2012) and the use of remote sensing. For example, Harvest Choice and the International Food Policy Research Institute (IFPRI) used NDVI from MODIS to derive a crop calendar data set at a 1 km resolution for sub-Saharan Africa (Guo, 2013; HarvestChoice, 2013) while Kotsuki and Tanaka (2015) used NDVI from SPOT-VEGETATION to develop the SAtellite-derived CRop calendar for Agricultural simulations (SACRA), a global crop calendar for 6 major crop types. A comparison of SACRA with MIRCA2000 and the product of Waha et al. (2012) showed large

Table 2
System outputs and dissemination by the various global and regional scale agricultural monitoring systems obtained from the questionnaire. Check marks or text indicate affirmative responses while a dash indicates a negative response or non-applicability.

Outputs and dissemination		GIEWS	FEWS NET	MCYFS	CropWatch	USDA-FAS	GEOGLAM	Seasonal Monitor	ASAP
Outputs from the system	NDVI profiles	✓	✓	✓	✓	✓	✓	✓	✓
	Rainfall profiles	✓	✓	✓	✓	✓	–	✓	✓
	Phenology analysis	✓	✓	✓	✓	✓	–	–	✓
	Anomaly analysis	✓	✓	✓	✓	✓	✓	✓	✓
Format to disseminate outputs	Bulletins	✓	✓	✓	✓	✓	✓	✓	–
	Reports	✓	✓	✓	✓	✓	–	✓	–
	GIS files	–	✓	–	–	–	–	–	✓
	Web services	✓	✓	✓	✓	✓	✓	✓	✓
System resolution to undertake assessment	Pixel level	✓	✓	✓	✓	–	✓	–	✓
	Administrative unit	✓	✓	✓	✓	✓	✓	✓	✓
	National level	✓	–	✓	✓	✓	–	✓	✓
Resolution of outputs	Pixel level	✓	✓	✓	✓	✓	–	✓	✓
	Administrative unit	✓	✓	✓	✓	✓	✓	✓	✓
	National level	✓	–	✓	✓	✓	✓	–	✓
	Other	–	Livelihood zone	–	–	–	–	–	Global overview
Timing to release system findings	During the growing season	✓	✓	✓	–	–	During the growing season on the first Thursday of the month (in line with AMIS Market Monitor publication schedule)	✓	✓
	Monthly	✓	–	✓	–	✓	✓	–	✓
	Other	–	Every dekad	–	Quarterly and annually	Numerous maps and charts updated every dekad	–	3 per season (as a goal)	Automatic warnings every dekad (10 days) and monthly country level analysis

discrepancies in places; hence it was not possible to determine which product was the best overall. Developed from an agricultural monitoring perspective, Whitcraft et al. (2015a) used 10 years of NDVI from MODIS to identify the start, peak and end of the agricultural growing season for all major crops together at a resolution of 30 arcmin. This product is useful for identifying the periods during which cropland areas should be monitored by EO, thereby informing strategies for image acquisition. ASAP also makes use of remote sensing based phenology from 15 years of MODIS data and the outputs have been compared with FAO and USDA national level crop calendars to derive sub-national calendars. ASAP uses and re-distributes the sub-national crop calendars for all administrative units where there is a match between the remote sensing based phenology and FAO/USDA crop calendars. The GIEWS ASIS system uses phenology from a time series of longer than 30 years from METOP and NOAA AVHRR (1984-present).

The lack of calibration and validation data sets that adequately represent geographic diversity and spatial and inter-annual variability in sowing and harvesting dates has slowed the advancement of remote sensing-based approaches. Therefore, the establishment of an openly accessible database of samples of sowing and harvesting dates across major and minor agricultural areas of the world and across multiple years would greatly advance the use of remotely sensed information in agricultural phenology, which would bolster the entire enterprise of EO-based cropland monitoring. Crowdsourcing and self-reporting by farmers may also provide more phenological data in the future.

4.1.3. Maps of cropping intensity (CI)

Cropping intensity (CI) refers to the number of crops grown within a year, and can provide valuable information regarding food security (Jain et al., 2013). Both FEWS NET and WFP's Seasonal Monitor view information about CI as very critical while four other systems viewed this information as critical. There have been a number of studies using remote sensing to determine CI in Asian countries (Jain et al., 2013; Gray et al., 2014) and China in particular (Qiu et al., 2014; Yan et al., 2014; Ding et al., 2016; Qiu et al., 2017) but there is currently no global data set available (Iizumi and Ramankutty, 2015). Using only MODIS data, Gray et al. (2014) found that they underestimated the number of cropping cycles due to missing data, particularly during cloud-covered monsoon periods, and recommended the use of data from multiple sensors. Other studies have shown the importance of adding other types of data such as agricultural statistics or outputs from crop models (e.g. Qiu et al., 2014). Although the agricultural statistics from FAO implicitly contain information on multiple cropping in the total production and area harvested figures, the CI data are not recorded (Iizumi and Ramankutty, 2015). Thus, it is important to build a global database with this information, both nationally and at the sub-national level, to aid in the development of global maps of CI.

4.1.4. Maps of crop type

Maps of crop type were viewed as very critically important by half of the systems and critical by two others. Neither the ASIS system of GIEWS or the MCYFS of MARS uses crop type information; in the case of MARS, agricultural statistics are used instead. Spatially explicit crop type maps have been produced by downscaling national and sub-national statistics using different methodologies. The M3 Cropping System Model (Ramankutty et al., 2008) consists of harvested area and yield downscaled for 175 crops including tree crops and managed grasslands. Using remote sensing, cropland and pasture maps are constructed at a 5 arc-minute resolution and national and sub-national agricultural data are then downscaled using a regression approach. The MIRCA2000 data set is a downscaling of 26 crops for rainfed and irrigated systems (Portmann et al., 2010) and uses the M3 data as a starting point. It also

Table 3
Additional characteristics of each of the agricultural monitoring systems obtained from the questionnaire, including the role of the analyst, dealing with information disagreement, GIS outputs, area covered, the main customers and interactions between the systems.

Other system characteristics	GIEWS	FEWS NET	MCYFS	CropWatch	USDA-FAS	GEOGLAM	Seasonal Monitor	ASAP
Role of the analyst in the system	Integrate meteorological data with vegetation indices, prices and other ground information to assess food security situation	Provide agrometeorological analysis and crop condition classification	Perform agro-meteorological and statistical analyses, judgement and selection of statistical results	Synthesize all of the data inputs and try to explain any strange results from the indicators	Collect relevant supplemental data, aggregate, make determination on most likely outcome of harvested area and yield (i.e. production) and revise every 30 days as conditions change	Examine multiple data layers from RS and ground data, bring in their field-based or local expertise and submit conditions on a monthly basis. Participation via teleconference and drafting of the Crop Monitor where consensus is reached	Prepare narrative reports based on system outputs	Occurs in the second step of the workflow with the expert analysis at the country level. Executed monthly for all countries with at least one sub-national unit (for crops or rangeland) with warnings
Action taken when different sources disagree	When there is no convergence of meteorological indicators, the analyst contacts the Ministry of Agriculture and cross checks with prices and other socio-economic data	A convergence of evidence approach is taken where field reports take precedence over remote sensing	Expert judgement	Analyze reasons for disagreement, then weighting to reach consensus	Long standing work flow incorporating iterative meetings with agricultural economists and specialists, multi-stage review process prior to each monthly publication of global crop expectations	The Crop Monitor Coordination Team evaluates discrepancies and consults with experts, EO and other sources of evidence, then discussed in monthly teleconferences where an evidence based consensus is reached	Observations take precedence but diagnostic confidence is decreased	Compare all internal and auxiliary information and expert evaluation
Open GIS output	FAO GIEWS is providing for the country-level ASIS via FTP VCI and TCI only. We are users of most of the GIS data.	Yes, downloadable from websites	No	Yes, downloadable from websites	GIS outputs are meteo and NDVI maps, some have world files associated	No	Plots and time series data are openly available. Other data sets are being prepared to be open	All system outputs downloadable
Area covered by the system	Global	Sub-Saharan Africa, Central Asia, Central America and the Caribbean but data sets offer global coverage	Europe and neighboring countries including Russia, Kazakhstan and China	Global for agroclimatology, regional for farming activities, crop condition, production and yield for 31 countries	Global	G20 + 7 countries for Crop Monitor for AMIS, Crop Monitor for Early Warning covers countries most at risk of food insecurity (Central America, all of Africa, and large parts of Asia)	WFP regions (near global)	Dekadal automatic warnings are global. The monthly assessment is done for 80 countries
Main customers of the system	FAO and FAO member countries	Food security analysts	DG Agriculture, Eurostat, national stakeholders, agricultural ministries, press, insurance companies, international organizations, GEOGLAM, AMIS	State Grain Administration from China and other government departments but also other countries download the bulletins	International and domestic commodity trade, brokers, shipping, many in the commodity food value chain	AMIS, National Ministries of Agriculture, international aid organizations/early warning community, in some cases, agribusiness (e.g. future traders, reinsurance)	WFP management and offices around the world. Others if useful	Main customers are colleagues in DG DEVCO, ECHO and EU delegations, but the system is open to the food security analyst community

(*continued on next page*)

Table 3 (*continued*)

Other system characteristics	GIEWS	FEWS NET	MCYFS	CropWatch	USDA-FAS	GEOGLAM	Seasonal Monitor	ASAP
Interactions with other global agricultural monitoring systems	Use information from FEWS NET. Contribute to GEOGLAM Crop Monitor	Contribute to GEOGLAM Crop Monitor	Contribute to GEOGLAM Crop Monitor	Some baseline data from MARS and FAO are shared. Contribute to GEOGLAM Crop Monitor	If time permits analysts review other systems. Ingest publically available forecasts for data visualization of current and past crop estimates from multiple sources. Contribute to GEOGLAM Crop Monitor	Interactions with FEWS NET, GLAM, USDA-FAS, China CropWatch, JRC MARS. National monitoring systems participate (e.g. Argentina, Brazil, South Africa, Tanzania, Uganda, Kenya, etc.), and regional/ multinational systems (e.g. IGAD/ICPAC, Asia Rice, etc.)	Contribute to GEOGLAM Crop Monitor	The information is the basis for the JRC contribution to the GEOGLAM Crop Monitor. There is also a collaboration on methods with WFP (e.g. time series smoothing algorithm) and with ASIS (use of SPIRITS modules)

EU = European Union, DG DEVCO = Directorate-General for International Cooperation and Development, DG ECHO = Directorate-General for European Civil Protection and Humanitarian Aid Operations, SPIRITS = Software for the Processing and Interpretation of Remotely Sensed Image Time Series, IGAD = Agricultural Data Interest Group, ICPAC = IGAD-Climate Prediction and Application Center, EO = Earth Observation.

provides a further temporal disaggregation by month. The SPAM product (You et al., 2014) uses a cross-entropy approach to downscale area and yield for > 40 crops into high-input irrigated, high-input rainfed and low-input rainfed production systems using additional information such as crop prices, population density and suitability. Products are available for both 2000, which used the M3 cropland extent as an input, and 2005, which uses the IIASA-IFPRI global cropland map (Fritz et al., 2015). The Global Agroecological Zones (GAEZ) cropping system model has produced gridded harvested area and yield by downscaling agricultural statistics for 23 crop types using an approach similar to SPAM although the underlying cropland extent is based on suitability. Anderson et al. (2014) compared these four products and found large discrepancies between them, which are caused by differences in the input data used, in particular the underlying cropland extent, as well as the methodologies used for downscaling. Hence there are clear uncertainties in all of these products and only the SPAM data set is being updated every 5 years.

Remote sensing is another approach for constructing maps of crop type (Boryan et al., 2011), which holds more promise for the construction of annual crop type maps globally on an operational basis. However, much of the crop type mapping to date has used MODIS data and has only been demonstrated on test areas (Wardlow and Egbert, 2008; Ozdogan, 2010; Brown et al., 2013). More recently, Salmon et al. (2015) have produced a global map of irrigated, rainfed and paddy croplands using various MODIS products and other agroclimatological data but this does not include the major crop types except for wetland rice. Inglada et al. (2015) have developed a processing chain for creating crop type maps at the global scale using Landsat and SPOT data, which has also been applied to Sentinel 2 data as part of the Sen2Agri project for Ukraine, Mali, South Africa and selected sites in other countries around the world with the aim of creating operational systems that can support GEOGLAM. Combining MODIS and Landsat data, high resolution soybean maps of the United States and Argentina have been constructed (King et al., 2017; Song et al., 2017). The integration of data from SAR (Synthetic Aperture Radar) with optical data also holds promise for crop type mapping as demonstrated by McNairn et al. (2009) in the construction of an operational annual crop inventory in Canada. While the methodological ability to derive crop type maps from time series of satellite images has been intensively demonstrated, the lack of seasonal calibration data for the classification appears as the main constraint to operationalization (see section 4.1.7).

4.1.5. Crop management data sets

Five systems rated crop management data sets as critical while the remaining systems viewed this as less critical data. However, there is a clear lack of data on crop management practices, which are key factors that influence agricultural productivity, and spatially-explicit data sets are needed for crop growth models, which can simulate yields under different management practices. From an inventory of the main data sets available for different land management practices, Erb et al. (2017) highlighted the lack of data on tillage and nitrogen fertilization. Currently no data on tillage are available although promising approaches are being developed using Sentinel 1 (Atstaja, 2017) while there are spatially explicit global data sets on nitrogen fertilization (Liu et al., 2010; Potter et al., 2010; Mueller et al., 2012). These data sets are, however, derived from models, and they show large discrepancies between them. More recently, Lu and Tian (2017) downscaled national nitrogen and phosphorus use to a 30 arcmin resolution to create a gridded time series from 1961 to 2013. There are also a number of uncertainties with this data set, e.g. it does not take grassland fertilization into account so may overestimate fertilizer use in some areas, and the M3-crop distribution data set was used for crop types, which may lead to further uncertainty in the estimates.

Crop management practices may also adversely affect the environment. Salinization, eutrophication and contamination of areas surrounding cropland, e.g. rivers, ground water but also populations of

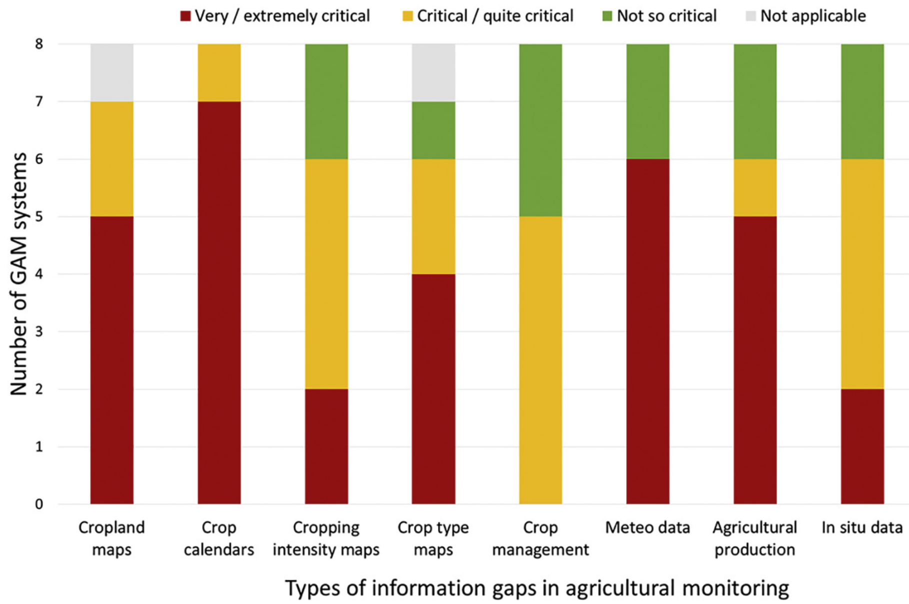

Fig. 3. The level of importance of different types of information for agricultural monitoring.

natural pollinators, are affected by over use of pesticide, and are common environmental problems related to agriculture. To understand their effect on the environment, researchers usually have to piece together information on fertilizers, pesticides and their dosages and frequency. A clear registry and characterization of these and other environmentally related practices from cropping areas in the world would be useful for building better spatially explicit products of crop management practices but also for evaluating their impacts on the environment, including soil health, water quality and biological activity around and in crop fields.

4.1.6. Meteorological data

Six out of eight systems viewed meteorological data as being very important for their system performance where rainfall data are the most critical meteorological input. Rainfall estimates are used by all eight monitoring systems (Table 1). Although the most accurate rainfall is obtained from rain gauges, the spatial network of stations is too sparse, particularly in places where food security risks are greatest, creating spatial data gaps across many areas (Maidment et al., 2017). In general, the global meteorological station network has diminished and deteriorated in some developing countries, in particular Central Asia, and many stations cannot be maintained due to underfunding and insufficient national capacity (Rogers and Tsirkunov, 2013). To complement ground-based meteorological data, and rainfall in particular, spatially explicit measurements can be obtained from atmospheric circulation models and satellite observations, e.g. precipitation forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF), the rainfall estimates from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) of the USGS, rainfall from the Tropical Rainfall Measuring Mission (TRMM) and the Tropical Applications of Meteorology using SATellite (TAMSAT), among others. Maidment et al. (2014) provide a comprehensive overview of available gauge and satellite rainfall data for Africa and compare seven different rainfall products, showing there are disagreements when compared with one another and with rain gauge data. There is clearly a tradeoff between products that incorporate rain gauge data but have shorter historical records compared to those with longer historical records but which do not use rain gauge information. Hence there are uncertainties around these products, which are further propagated in crop models that use satellite-based rainfall estimates. Rainfall estimation using radio interference in cellular networks (Overeem et al., 2013) is a promising avenue of ongoing research that may benefit agricultural monitoring in the future. Moreover, there are recent plans to increase the density of meteorological observations by deploying low cost sensors and by using cell phone towers as sites for meteorological stations (Rogers and Tsirkunov, 2013).

4.1.7. Data on agricultural production, area and yield

Six out of eight systems view this information as very critical or critical. The FAO has been compiling statistics relevant to agriculture in its FAOSTAT system for 245 countries and 35 regions from 1961 to the most recent available year (FAO, 2015b). The data sets are based on censuses, agricultural samples and questionnaire-based surveys (FAO, 1996). Despite this vast historical record, there are several drawbacks of relying on the quality and accuracy of such national reports as there have been no attempts to harmonize data collection methods among the different countries (World Bank and FAO, 2011). National agricultural statistics are generated by many countries but their accuracy, timeliness and consistency over time and accessibility vary greatly. Some countries collect administrative data based either upon census, surveys or national sampling frames. Area frame sampling is a well-established statistical method for collecting agricultural data that cannot be obtained directly by satellite such as actual crop yield (Gallego, 2015). However, other countries have no established formal data collection process and there are no globally recognized standards for in-situ or survey data collection of agricultural statistics (Justice and Becker-Reshef, 2007).

Since FAO statistics are reported nationally, FAOSTAT only provides limited information on agriculture, particularly when spatially explicit data are required (Anderson et al., 2014). The lack of sub-national agricultural statistics has been identified as a challenge to crop forecasting systems and remote sensing (Kayitakire, 2012). However, there are initiatives such as Agro-MAPS (Mapping of Agricultural Production Systems) to collect statistics on crop production, area and yield at the sub-national level (FAO et al., 2006) and FAO's CountrySTAT[11]. Many researchers have also compiled sub-national statistics for many countries and crops as part of their studies, e.g. Ray et al. (2012), where the data should be placed in open data repositories for sharing.

More in-situ yield data are needed to develop and validate crop models, which are used to make forecasts of production, or as inputs to

[11] http://www.countrystat.org/.

statistical models for prediction of yield anomalies using remote sensing. Six out of eight systems viewed in-situ data as critical to very critical for their operation. The Land Parcel Information System (LPIS) is openly available in some countries across the EU, e.g. the Netherlands and Czech Republic, which may encourage other countries to open up their agricultural databases in the future. There are also sources of in-situ yield data available from crop trials, e.g. from FAO (van der Velde et al., 2013), the International Maize and Wheat Improvement Center (CIMMYT), the Global Yield Gap Atlas[12], and the Global Agricultural Trial Repository and Database[13] hosted by the CGIAR's (Consultative Group on International Agricultural Research) Research Program on CCAFS (Climate Change, Agriculture and Food Security). The latter initiative is aimed at encouraging scientists to share their data within the community, where these data might otherwise remain locked within their own institutions (Smith et al., 2015). Advances in mobile phone and location-based technologies are also increasing the in-situ collection of yield data while the private sector is another potential source of data. However, the sharing of and access to these diverse data sets is not common.

Crop growth models also require soil information as a critical input (Krishna Murthy, 2004). For yield forecasting for agricultural monitoring purposes, the Harmonized World Soil Database v1.2 (Nachtergaele et al., 2010) is available at a 1 km resolution, which has integrated existing regional and national soil data sets, many of which are available from the International Soil Reference and Information Centre (ISRIC). However, this map has been criticized for its coarse resolution and the fact that it does not represent the current soil condition but rather combines existing soil data sets from different time periods and of differing quality (Sanchez et al., 2009; Grunwald et al., 2011). Several other data sets of interest are available from ISRIC such as the Harmonized Global Soil Profile data set v3.1, containing > 10 K soil profiles globally, gridded data sets of soil water capacity and the more recent SoilGrids250m product (Hengl et al., 2017).

4.2. Gaps in methods

Although Jones et al. (2017) argue that data scarcity and limitations are more important than gaps in theory and approaches in agricultural system models, there are still missing pieces in the science behind agricultural monitoring and forecasting. To better understand these issues in the context of this paper, the eight global agricultural monitoring systems were surveyed for their perceptions regarding current methodological gaps. Three of the systems mentioned the need for better predictions of yield and crop production, which can either be realized through crop growth models or statistical models, e.g. based on NDVI. The review of agricultural system models by Jones et al. (2017) highlighted several recent reviews of crop models and their limitations, mostly related to the data but also recognizing the need for continued methodological developments.

Gaining a better understanding of the differences between different input data sets is another gap that was identified. For example, precipitation varies between different sources; the same is true of different vegetation indices. Having a better understanding of where these data sets have discrepancies and why is very important for consensus in monitoring, and the tools for carrying out an automated comparison are currently lacking.

Two other relevant points were raised. Some felt that it is not so much the methods that are lacking, since there is considerable scientific research taking place in many different areas related to agricultural monitoring, but rather the ability to operationalize these new methods. Hence there is a lag time between the emergence of scientific research and implementation as operational activities. The second point is related to lack of tools or methods for synthesizing the variety of information coming into the system for decision makers, which was also raised as a key issue by Jones et al. (2017). They mention the idea of a virtual laboratory in which scenarios could be defined under different spatial and temporal scales, which could produce outputs suitable for decision makers but which does not currently exist. Such tools should also allow inputs to the system to be weighted differently depending on the situation, e.g. a normal year versus a drought year, which was another comment raised in the survey.

5. Conclusions

This paper compared eight global and regional scale agricultural monitoring systems that are currently supporting efforts to improve the world's food security. The results of a questionnaire show that there are many similarities between them, in particular in their use of meteorological data and remote sensing. However, the systems are tailored to meet the needs of different customers and hence they differ in the importance they place on inputs to the system as well as how they disseminate their results.

Data recorded by remote sensing satellites mainly assist with the assessment of crop condition and crop condition anomalies, which can then be used to infer information on yield, area and production reductions. However, this approach is not able to provide quantitative crop area and production forecasts as ideally needed for food security interventions. Crop growth and yield forecasting models are data intensive (daily meteorological inputs needed) and are currently applied only for the US by the USDA system and for Europe by the MCYFS. Moreover, remote sensing-based methods for agricultural statistical forecasting need historical archives of high quality statistics, which are not available in all countries.

All global systems and in particular those covering food insecure countries use only remote sensing-based crop condition monitoring or basic water balance models. Crop production and area information in these countries is largely based on local expert knowledge (eg. USDA-FAS, FEWSNET and GIEWS). Also for the remote sensing-based monitoring systems, gaps in their baseline information are well documented. Moreover, when different basic (global) products are compared, e.g. cropland extent, crop types or rainfall estimates, they often show large differences. Hence knowing which product to use in an environment where more and more products are appearing remains a challenge.

Within the context of crop condition monitoring and yield forecasting, moderate resolution data (10-100 m) has not achieved broad scale adoption across the globe, primarily due to the lack of consistent cloud free acquisitions with sufficiently high temporal resolution (Whitcraft et al. 2015b), but also due to barriers in operational adoption of EO-based methodologies related to gaps in technological expertise and challenges in accessing, downloading, storing, and managing the sizable data volumes this resolution produces. The GEOGLAM initiative has demonstrated that this is a priority growth area for analyses spanning the extent of cropland for fields of all sizes. GEOGLAM works closely with the Committee on Earth Observation Satellites (CEOS) – a consortium of the world's civil space agencies – to confront issues of data acquisition, accessibility, and continuity. Examples of activity areas include developing data preprocessing standards to facilitate operational uptake of diverse data streams and cloud-based data dissemination systems and services. However, in order to make concrete progress towards enhancing the use of EO for agricultural monitoring, coordinated and complementary efforts to develop human and institutional capacity to use EO as they become increasingly available is equally critical. The transition of research-based methodologies to the operational domain hinges upon concerted efforts to document, preserve, and disseminate methods and guidance materials (i.e. training) to the broader agricultural community, a final step in research project timelines, which due to funding and scheduling constraints, is too often

[12] http://www.yieldgap.org/.
[13] http://www.agtrials.org/.

overlooked. Recently developed systems, however, are now making greater use of high resolution data in combination with cloud computing. This is the case, for example, for ASAP's high resolution viewer, which retrieves Sentinel 2 and Landsat imagery for any GAUL1 unit globally and computes NDVI anomalies. The combination of cloud computing with image enhancement and time series processing techniques developed in the past for lower resolution data are a highly promising way of exploiting recent remote sensing data, although the short archives remain a limiting factor for anomaly computation.

The launch of Sentinel 1, 2, 3 and Proba-V sensors addresses issues related to the availability of coarse and medium resolution imagery. For example, Sentinel 3 provides data at 300 m ground sample distance (GSD) and Proba-V at 100 m. Sentinel 2 already provides 10–20 m data at 5-day revisiting intervals although we still need archives for anomaly and change monitoring. The Venµs (Vegetation and Environment monitoring on a New MicroSatellite) sensor provides 12 spectral bands (at 5 m ground resolution) and a 2-day revisiting time. The hyperspectral HyspIRI will provide a spectral resolution of 10 nm, 19-day revisiting time and a spatial resolution of 60 m. Landsat 8, the Landsat data continuity mission (LDCM), includes two thermal bands for energy balance calculations, thereby providing new opportunities for crop monitoring (Atzberger, 2013). The German hyperspectral ENMAP will be launched in 2020. Finally, commercial image providers have also started to acquire hyper-temporal satellite image time series at < 10 m resolution with constellations of microsatellites. For example, Planet seeks to provide a daily coverage of the Earth's landmass at a 3-5 m resolution with the 175 + Dove satellites. However, as more of these big data streams from remote sensing are used for agricultural monitoring, more automated approaches such as that used by FAO-ASIS will be required.

Furthermore, as mentioned previously, in order to advance the state of the science, more consistent calibration and validation protocols for crop monitoring applications as well as the data sets to support them are needed. Logistically, this would involve the development of a coherent regional-to-global scale sampling scheme that accounts for geographic heterogeneity in climate and in cultivation practices, the routine collection of agreed-upon ground data, and the stewardship of such data sets to facilitate access to and use by the broader agricultural monitoring community. This would become an open in-situ data repository of data sets that are currently missing, e.g. planting and harvesting dates, crop types, irrigation, fertilizer and pesticide applications, etc. Such an effort would advance the state of the science by improving the robustness and applicability of remote sensing-based approaches to monitor croplands in a diversity of settings. Similar to the University of California at Irvine (UCI) Machine Learning Repository that maintains data sets for the machine learning community, an open repository of benchmarking data would also provide a one-stop-shop to test and compare new methods.

The increased amount of smartphones all over the world, even among low income farmers, usually the group responsible for the largest agricultural uncertainties, allows for increased opportunities to self-report geo-located crops and parcel practices, including planting dates, fertilizer application, irrigation and expected yields, through the use of purpose-designed mobile applications. Although information reliability can be a concern if self-reported information is used as the basis for global monitoring of agricultural production, ways to improve the precision and reliability of such information can be built into these applications. Such ways may include incentives such as feedback with timely agronomic and market recommendations, tailored to the registered crop and area where it is grown. Hence, it could be guaranteed that the majority, if not all the information provided, is as accurate as possible.

The food security and early warning community should also make greater use of the latent predictive capacity of social media and sources such as web search data (e.g. van der Velde et al., 2012) in the future. As an example, in 2016, farmers tweeted about their low, unexpected soft wheat yields, which were nearly 30% below the five year average and even lower than the yields obtained in 2003 that were affected by drought and heat waves. This situation was not picked up by early warning systems such as the MARS MCYFS so it represents an interesting source of ground-based information that can inform early warning systems.

Finally, we need to work towards greater sharing of data and information. GEO plays a pivotal role in encouraging member countries and organizations to share their data via the GEOSS Common Infrastructure but finding more ways to unlock data sitting in offices, hard disks and closed cloud systems remains a continuing challenge.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2018.05.010.

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